Implementation of Cognitive Driver Models in Microscopic Traffic Simulations

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ABSTRACT

In order to perform microscopic traffic simulations as realistically as possible, a detailed modelling of each individual driver is essential. Currently established microscopic traffic simulators follow a rather static approach to model the driver's behaviour. Individual emotional influences and temporarily occurring distracting factors are heavy to implement in the established state-of-the-art microscopic traffic simulators. This paper proposes a solution how emotional influences and distracting factors can be integrated in established traffic simulation tools. For this purpose, robot-learning approaches are adapted to model the emotional state of vehicle drivers. In the end of this work, a proof of concept is done to illustrate the strength of the developed approach.

Categories and Subject Descriptors

I.6.7 [**Simulation and Modeling**]: Simulation Support Systems

Keywords

Driver Behaviour Models, Cognitive Models, Distraction, Emotions, Microscopic Traffic Simulations

1. INTRODUCTION

Modelling the movements of individual vehicles as realistically as possible is an essential task of microscopic traffic simulators. The decision making process for each individual vehicle includes various domains, e.g. the present traffic infrastructure, the movements of other vehicles, or traffic cognition is rather rarely modelled in classic car-following models such as Krauß [19] or IDM [33]. There are approaches to model human behaviour via imperfection properties [19], however, this might not be sufficient to model the complex decision making process of human drivers. Especially, with classic car-following models it is not possible to simulate unexpected behaviour of drivers, such as short-time speeding, unexpected lane changes, distracted drivers, or visual impacts.

Moreover, perception is the basis for any further decision making and according to Schaub it is the *"transformation of physical and chemical stimuli to psychological processable information as foundation for action control"* [15]. Additionally, human perception is always related to individual objects on which the driver focuses and, consequently, a driver never has a complete view of the traffic situation and his/her surroundings. Not least because drivers perceive the *"outside-the-car"* world up to 90% by visual sense [6]. However, current microscopic traffic simulators do not consider these important visual senses, but rather apply perfect sight and senses to the driver. For a more detailed view it is important to consider the human factor. As Mesken identified, driving is a highly complex cognitive process which can not be simplified easily [21]. Additionally, drivers are highly influenced by emotions and distraction as a recent study shows [9]. For example, Sullman et al. [32] claim a rate of 40% distraction by inner factors while driving. Also, distraction caused by using the phone is the main risk factor of the 90% driver-related crash causations (emotion, distraction, fatigue, error) [9]. As essence of these studies, external and internal factors are identified which itself can be subdivided. Although drugs (including alcohol) have extremely high risk factor, they occur far less [9] but change perception and coordination dramatically. Table 1 summarises disrupting influences and the affected parameters of the driver.

In this paper, we introduce the consideration of emotional processes and distracting factors in microscopic traffic simulations. That is, each driver perceives his/her environment and assesses the traffic situation differently. Consequently, the resulting emotional state of the driver influences his/her decisions and behaviour. In addition, distracted drivers are modelled which also affects the driver's behaviour. Both

Effected Parameter	Influence: Distraction	Age	Drugs	External Factor	Driver Type
Visibility	*	*		*	*
Field of View	*	*	*		*
Estimation Error		*	*	*	*
Safe Distance	*		*	*	*
Acceleration					*
Deceleration					*
Reaction Time	*	*	*		*
Speed	*				*
Lane Behaviour	*				*

Table 1: Influences and Effects according to [9, 7, 26, 11, 35, 23, 17]

concepts and their impacts are implemented and investigated in microscopic traffic simulation environments.

2. STATE OF THE ART

For decades there has been research on the human thinking and decision making. General models specialised on the driving task have been developed and formulated in this period. Most of the models reference explicitly to the classical standards from Michon [22] and Rasmussen [25] who designed multi level models of human information processing. Those were merged by researchers like Edmund Donges [10].

The ITERATE project [16] and the DRIVABILITY model by Bekiaris et al.[3] both studied visual limitations of the perception of drivers. DRIVABILITY additionally considered environmental factors as road and weather conditions. The model of Yuhara and Tajima [36] took the influences of personal characteristics on perception into account. In addition, DRIVABILITY showed that emotions are a big factor that has to be considered. Deml et al. did research in the field of human behaviour characteristics and its representability in driver models. They analysed PELOPS and CosmoDrive as driver behaviour specific models in comparison to general cognitive approaches of QN-MHP and ACT-R [8]. However, neither of those models deal with emotional processes nor does any include temporary distraction (e.g. using the phone or configuring the car's navigation system). In context of representing cognitive processes in microscopic traffic simulations none of the models are suitable.

Analogous to Deml, Treiber implemented driver models in traffic simulators like VISSIM [5] and SUMO [18] which barely consider emotional processes and neglect distracting factors. The mostly used car following model IDM (Intelligent Driver Model) in combination with the lane change model MOBIL can be statically parametrised in terms of sportiness and cooperativeness, but do not yet consider cognitive processes as required [34].

Researchers and developers are beyond dispute about the recreation of human information processing principles in their models to match human behaviour. Therefore, our following concepts have the goal to implement the most important factors of cognitive modelling such as emotional processes and distraction in combination with existing car-following models.

3. CONCEPT

In the following, we present our concepts which introduce the consideration of emotional process and distracting factors in microscopic traffic simulation.

3.1 Distraction

Research has shown internal and external factors that distract and impair drivers [9]. All factors consider a different or for a short time not existing view on the surrounding environment. While people perceive the world at 90% visually [6] [29] the additional 10% can be neglected. Therefore it would be an asset to modify the raw simulation data according to the type of distraction.

Firstly, the *maximum visibility* of a driver is reduced based on daytime, weather conditions, and personal visual performance. For example, glare can reduce visibility by up to 75% [31].

Secondly, the drivers *field of view* is always limited, mainly due to the car's pillars. As Renge et al. researched elderly people lose their head turning ability and have therefore a more narrow field of view [26]. During distraction, the field of view becomes tunnel vision due to the attention which is switched to the distracting task or factor. Figure 1 shows the a 360° field of view. It marks the driver's visible (translucent) and non-visible angles (black). This definition can be easily adapted for any new finding.

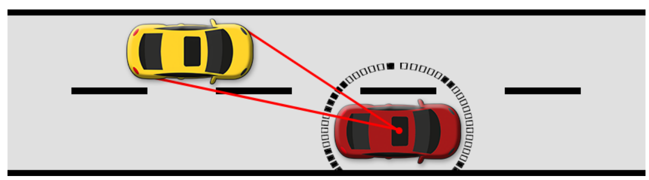

Figure 1: Field of view with non-visible parts (black)

Thirdly, drivers have to constantly estimate speeds, distances and headings of the surrounding vehicles in order to adapt speeds and make decisions. The *estimation error* depends on whether the driver is distracted and what type of driver he or she is. While simulation environments deliver exact values this error has to be included to generate human inaccuracy. This error can be generated randomly inside a previously defined range with the help of a smoothing function.

While both, visibility limitations and the estimation error need to be considered by the car-following model directly, there is also distraction caused by the driver which results in changes in the driving behaviour, according to Cooper et al. [7]. The most important consequences of distraction are massively longer reaction times (up to 100% longer). However, the reaction time is one of the basic factors that defines safety distance and therefore the capability of avoiding accidents. Figure 2 shows the effect of an extended reaction time. Additionally to the extended reaction time, a significantly higher variance in speed (up to 62.5%) can be found, lane changes are reduced, and drivers slip into short gaps while overtaking.

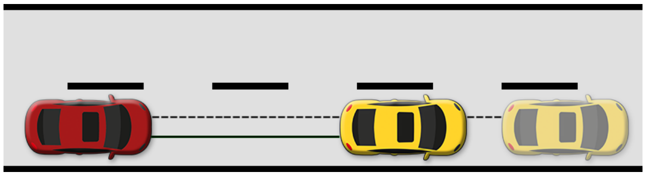

Figure 2: Effects of reaction time on safe distance. The leading vehicle was previously outside the safe distance and is now inside.

Accordingly, we propose to trigger short-time distraction randomly for each driver in the simulation. With a given distraction rate r_d the driver gets distracted for a short period of time more or less often. Given the distraction rate r_d, the current simulation time t_c and the time period t_w in which the distraction should take place, the next point of time t_d at which the driver gets distracted is calculated by equation 1. In order to prevent distraction triggered immediately after the previous distraction period has ended, a minimum pause t_p between two distraction events is used.

$$t_d = t_c + t_p + (1 - r_d) \cdot rand(0, 1) \cdot t_w \qquad (1)$$

Finally, each distraction lasts for several seconds in which the vehicle reduces its own speed a bit and is not able to accelerate.

3.2 Emotion

Based on current cognitive research, we propose to consider the emotional state of the driver and its effects on decision making in traffic simulations. Those emotional states are based on basic emotions, such as *anger*, *fear*, *sadness*, and *happiness* [12]. For modelling emotions and their effects, we use the *robot-learning-method* proposed by Gadanho and Hallam [14]. Here, the driver's perception of the traffic situation (*sensations*) as well as personal characteristics influence the *feelings* of the driver. Based on those feelings, the *dominant emotion* can be calculated which then affects the decision making process of the driver. Figure 3 shows the model used for calculating the dominant emotion based on sensations of the driver. This model is basically configured by the emotion coefficients C_{ef} which affect the influence of sensations to emotions, the activation and selection threshold I_{th_a} and I_{th_s} which is required for an emotion to be processed or selected, and the attack gain a_{up} and decay gain a_{down} which are used to increase or decrease the emotion intensities [14].

The following sensations are determined as the most important ones by us and therefore are included in the model. During the simulation for each sensation it is checked whether it is active or not. *Rear distance* determines if the car behind maintains the own preferred safe distance. If this sensation is active, it has increasing influence on the emotions anger and fear. *Duration* is a sensation based on Mesken [21], which tells if the driver's journey takes longer than expected. After a certain amount of time, this sensation gets activated and increases sadness and decreases happiness. The third sensation, *density*, depends on the own velocity and the traffic density. To determine if this sensation is active, the preferred safe distances of the car behind and in front is checked and whether the lane left to the vehicle is occupied or free. In such cases, it increases fear and

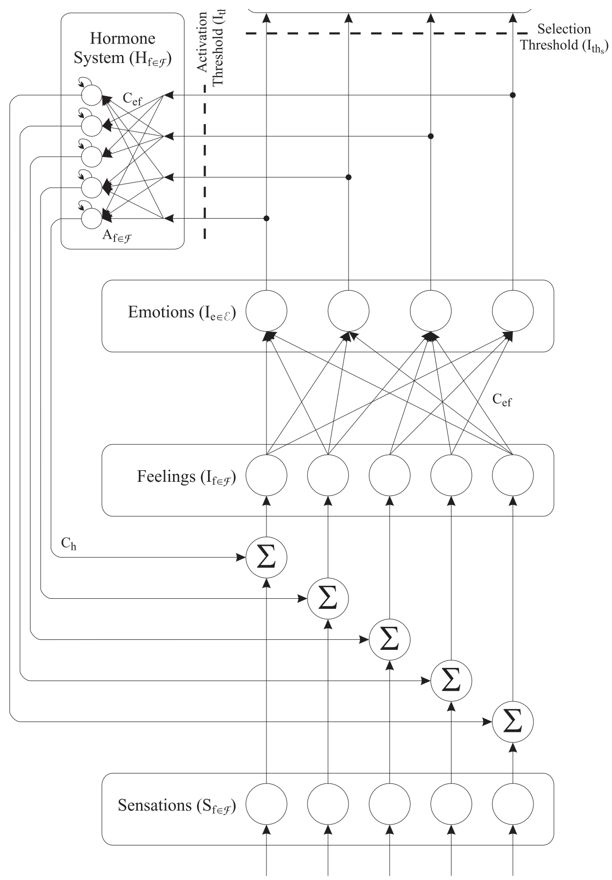

Figure 3: The emotion model (source: [14]) used for calculating the dominant emotion of the driver based on his perceptions.

anger, and decreases happiness. The last important sensation is *speed*, which tells whether the driver's preferred speed is achieved or not. If active, it has increasing influence on happiness, and decreases anger and sadness. As a result of those sensations, the emotion model calculates one dominant emotion which takes effect on the driver's behaviour.

Anger is considered to be the most frequent emotion and also has the most significant impacts on the driver's behaviour [13], especially on gaining speed and decreasing the safe distance [2]. Furthermore, we propose to adjust the properties of the lane change model in a way, that it is more aggressive, e.g. by deactivating cooperative lane changes and keeping the vehicle on the most left lane.

The emotion *fear* results in the need to increase safety which leads to a reduction of the speed by 20% [20] and the wish to change onto the most right lane. Furthermore, a frightened driver is not willed to adapt his speed to the leading vehicle but maintains his own reduced speed, and keeps more distance between his and the leading vehicle.

Sadness results in strategies to avoid any risks [1, 21], such as decreasing speed and a passive lane change behaviour. The passive behaviour includes cooperative lane changes and an adaptation to the speed of the leading vehicle.

A *happy* driver is ready to gain speed due to this emotion [4]. Accordingly, the preferred speed is increased by 10% which might lead to an exceedance of the allowed speed.

The driver respects other drivers and is willed to adapt his speed in order to act cooperative, which can be realised by adjusting the properties of the lane change model.

3.3 Driver characteristics

Furthermore, next to the consideration of distraction and the emotional state of drivers, we propose to take individual driving characteristics into account. Therefore, three different driver types are defined: *sporty*, *normal* and *cautious*, based on [17]. For each type, different properties can be parametrised according to Schulz et al. who did their research on driver assistance systems [27]: Preferred maximum speed v_{max}, default acceleration a_{acc} and deceleration a_{dec}, the speed factor f_s, and the preferred safety time gaps to the leader and follower t_{gap} describe the basic parameters of the car-following model in the traffic simulation. The politeness factor p is adapted from the lane-change model MOBIL and presents the willingness to collaborate with other vehicles [33] during lane changes. Moreover, each driver type is parametrised with distraction rate r_d.

4. PROOF OF CONCEPT

In order to prove our concept, we choose to simulate a scenario with the proposed modules with the help of the simulation framework *VSimRTI*, which is a flexible framework to simulate and assess complex simulation scenarios on microscopic and mesoscopic level. The main focus of VSimRTI is on coupling different simulators with different emphases [28, 24]. Through the interplay of these different simulators it is possible to conduct investigations in the context of cognitive sciences, such as the viewing of distractions and emotions that may occur during a journey. For our scenario, we coupled VSimRTI with the microscopic traffic simulator *SUMO*, which provides the possibility to use different car-following and lane-change models. By using the socket interface TraCI, it is also possible to interact with the vehicles and their parameters during the simulation. However, this interaction is encapsulated in VSimRTI completely, which allows us to use a high-level API in order to implement the proposed models. This also enables the possibility to replace the traffic simulator in further investigations.

4.1 Parametrisation of drivers

After defining vehicles and their journeys, the drivers need to be parametrised according to the properties in section 3.3, as seen in table 2. Additionally, in order to configure the emotion model, the emotion coefficients C_{ef} found in table 3 are used for our simulations. For example, the emotional value of *anger* is increased by 70% as soon as the sensation *rear distance* is triggered, whereas it is decreased by 10% if the sensation *speed* is active. Further parameters of the emotion model have been configured with the values proposed by [14].

4.2 Traffic Scenario

The scenario to be evaluated represents a familiar commuter route in the urban area of Berlin. Most of the vehicles are emitted along the motorway BAB115 heading north and passing the intersection between BAB115 (AVUS) and BAB100, which is one of Germany's most frequent traffic nodes. Therefore, the focus lies on this bottleneck, as seen in figure 4. Next to this, several vehicles are driving on other motorways in this area, to produce a traffic distribution close to reality. However, we do not have any traffic flow data or realistic origin-destination matrices and therefore we decided to use artificial traffic flow for our simulations. In total, 3,200 vehicles are emitted on four starting points within a simulation period of 3,600 seconds.

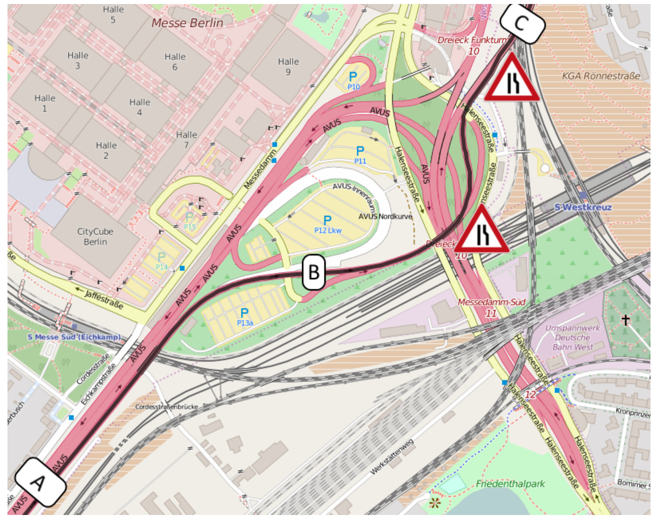

Figure 4: Traffic scenario with route and bottleneck at motorway interception and following on-ramp situation. Also, vehicle flow detectors A, B and C are placed before, along, and after the bottleneck. (Map source: OpenStreetMap)

	Driver type		
	sporty	**normal**	**cautious**
v_{max}	160 km/h	140 km/h	120 km/h
f_s	1.1	1.0	0.9
a_{acc}	5.0 m/s^2	3.0 m/s^2	2.0 m/s^2
a_{dec}	10.5 m/s^2	8.5 m/s^2	6.5 m/s^2
t_{gap}	0.8 s	1.7 s	2.8 s
p	AGGRESIVE	COOPERATIVE	CAUTIOUS
r_d	10%	20%	5%

Table 2: Individual parametrisation of vehicles based on driver types.

Emotion	*rear distance*	*duration*	*density*	*speed*
anger	0.7	0.0	0.1	-0.1
fear	0.2	0.0	0.8	-0.1
sadness	0.0	0.3	0.0	-0.2
happiness	0.0	-0.2	-0.1	0.4

Table 3: Emotion coefficients C_{ef} used for our simulations.

4.3 Simulations

In order to examine the various concepts proposed by us, we execute several simulations. The following simulation configurations are used:

0 Plain simulation **without** different driver types, **without** emotions, and **without** distraction triggering. in this simulation run, each driver is parametrised the same, that is with the values of the *normal* driver.

1 This simulation run includes **different driver types** in the simulation, **without** emotions and **without** distraction triggering. 65% of the vehicles are parametrised as *normal*, 15% as *cautious*, and 20% as *sporty* drivers, based on [17].

2A This simulation run includes **different driver types** in the simulation and considers **emotions** for each driver, but still **without** distraction triggering. The drivers are parametrised and distributed the same as in **1**.

2B This simulation run includes **different driver types** in the simulation and triggers **distraction** for each driver. This simulation run is **without** considering emotions. The drivers are parametrised and distributed the same as in **1**.

5. RESULTS

For each simulation run, several measurements are examined. For this purpose, we set up induction loops A, B and C on important points along the main route (see figure 4) in order to observe the traffic flow during the simulation and the distribution of vehicles among lanes. Furthermore, general properties such as the duration of journeys and the average speed of vehicles are measured. Those measures are used to compare the simulation outcomes in order to analyse the impacts of the different domains *driver types*, *emotions*, and *distraction*.

In table 4 general measurements of the different simulation runs can be found. For each vehicle, the travel time and the average speed during the journey is measured. Additionally, the time loss property shows how much time the vehicles lost in average compared to the ideal travel time they would achieve without any traffic. For example, a high value in time loss can indicate dense traffic or even congestion. Furthermore, for the simulation runs which have been mapped with different driver types, the measurements are additionally segmented for each type. Note: 300 vehicles which were inserted at the beginning of the simulation are excluded since they would distort the results.

Figure 5 shows the average speed at all detectors placed along the route. With the help of this, traffic congestion can be identified. For example, it can be seen that the density at detector B is very low as soon as distraction is triggered in the simulation.

Furthermore, figure 6 shows the distribution of vehicles among lanes at detector A. According to [30], a typical lane distribution on a motorway with a total flow of 2,000 veh/h is 33% of the flow on the left lane, 28% on the right lane, and 39% on the middle lane. This distribution can be achieved the best by the simulation which considers different driver types and emotions.

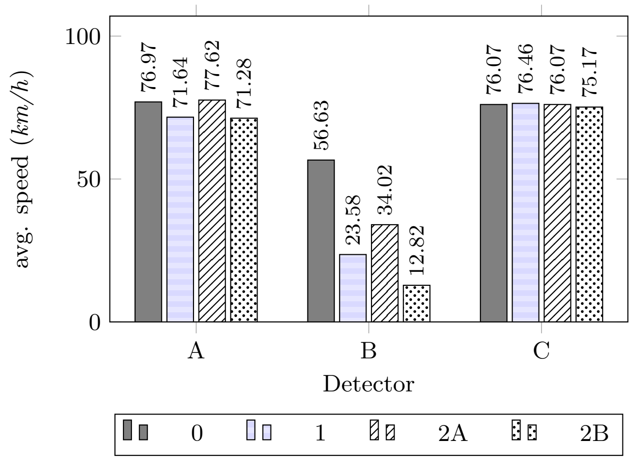

Figure 5: The average speed in km/h of all vehicles passing detectors A, B and C for each simulation run. Amongst other things, congestion can be found at detector B if drivers are parametrised individually.

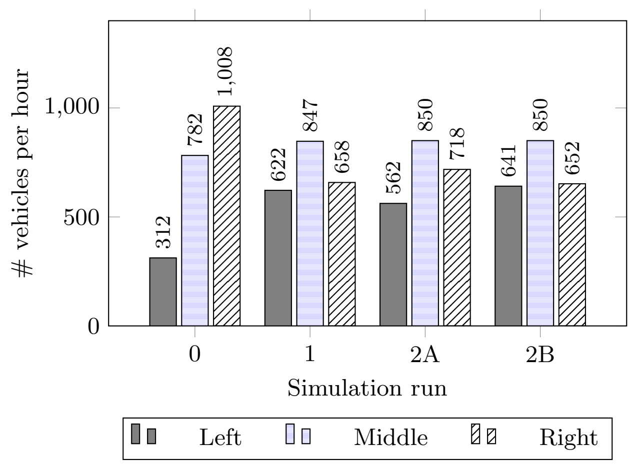

Figure 6: Traffic flow on the different lanes at detector A (AVUS) for each simulation run. It can be seen that a diverse traffic with different driver types leads to a more realistic distribution of traffic on different lanes.

5.1 Configuration 0 - Plain simulation

In this simulation all vehicles are parametrised with equal values and do not differ from each other. There is no traffic congestion throughout the simulation and vehicles can reach their preferred speed during the whole journey. This can be shown by the low average travel time of 650 s and a low value of time loss, which is only 61 s. Due to the constant traffic flow at the bottleneck at detector B, the vehicles can perfectly merge onto the only existing lane without producing any congestion while keeping the maximum allowed speed. Concluding, this simple simulation results in a quite perfect flow of vehicles which is, however, not realistic. Vehicles follow each other perfectly without overtaking, which leads to an unrealistic lane distribution where the left lane is used rarely.

Simulation Run	**0** Plain simulation	**1** Driver types	**2A** Driver types + Emotions	**2B** Driver types + Distractions
All drivers				
Avg. speed in km/h	76.18	71.35	77.72	66.17
Avg. travel time in seconds	650	695	646	780
Avg. time loss in seconds	61	107	95	191
Cautious drivers				
Avg. speed in km/h	-	67.46	73.62	63.00
Avg. travel time in seconds	-	726	676	795
Avg. time loss in seconds	-	72	79	141
Normal drivers				
Avg. speed in km/h	-	71.46	77.62	66.64
Avg. travel time in seconds	-	694	646	770
Avg. time loss in seconds	-	105	94	180
Sporty drivers				
Avg. speed in km/h	-	74.02	81.11	67.03
Avg. travel time in seconds	-	676	622	802
Avg. time loss in seconds	-	141	111	266

Table 4: Results for the different simulation runs

5.2 Configuration 1 - Different driver types

This simulation run introduces different driver types: *normal* (65%), *cautious* (15%), and *sporty* (20%). With this configuration, the traffic flow is much more diverse than in the previous run. A more diverse parametrisation of vehicles results in traffic situations one would expect to find in reality, such as overtaking vehicles, forming of vehicle groups and short-living traffic congestion at bottlenecks (e.g. at detector *B*). This is emphasised by a much better lane distribution at detector *A* (figure 6), which almost meets the typical lane distribution on motorways.

Not surprisingly, the effects of the parametrisation of different driver types can be found in the simulation results as well. Cautious drivers have the lowest speed and longest travel times, while sporty drivers reach their targets fastest. On the other side, cautious drivers have the lowest time loss since their ideal travel time is already high. However, it can also be seen that the average driver is slower than in the previous simulation. This can be explained by the cautious drivers which slow down all other vehicles as well, and by the short-living traffic congestion at the bottleneck (detector *B*).

5.3 Configuration 2A - Driver types and emotions

As previously, vehicles are parametrised in this simulation run. Additionally, the emotional state of each driver is modelled (according to chapter 3.2). The overall flow is very similar to the previous run, where vehicles form groups and traffic congestion occurs. However, it can also be seen that the average driver is much faster and that his journey takes less time. This effect can be explained by the emotional state of the driver.

In order to study the emotional state of the drivers and its influence on the traffic, figure 7 shows the distribution of dominant emotions during the simulation. While *normal* drivers are mainly *happy* since they can reach their preferred speed on the major part of their journey, cautious drivers often show *anger* because of other vehicles which come very close from behind. However, both *anger* and *happiness* result in an increasing speed factor which therefore increases the average speed of all drivers. This also allows sporty drivers to drive faster than usual. Furthermore, the emotion *anger* lets drivers speed up more than allowed. While the speed is limited to 100 km/h on the AVUS, vehicles with sporty drivers occasionally speed up over 120 km/h for a short time, until *happiness* suppresses *anger*. Concluding, modelling the emotional states and its reactions can result in unexpected driver behaviour which is closer to reality.

Furthermore, the general traffic flow is not negatively affected. Actually, the average speed at detector *B* increases due to aggressive lane changes of sporty and *angry* drivers. In addition, the lane distribution at detector *A* matches the usual distribution which can be found at three-lane motorways with a flow of 2,000 vehicles per hour [30].

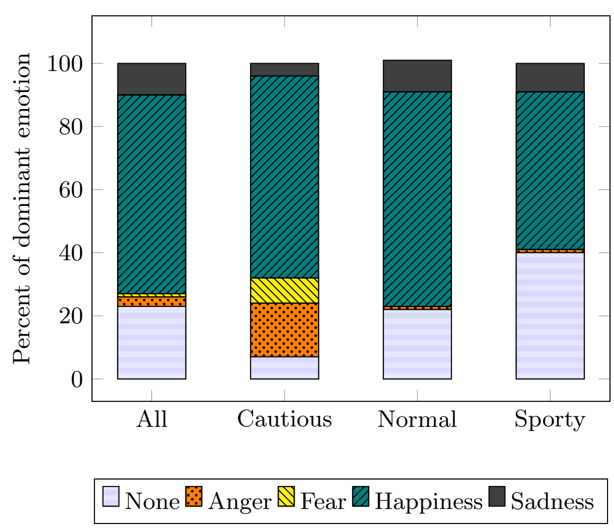

Figure 7: Distribution of dominant emotions in the simulation.

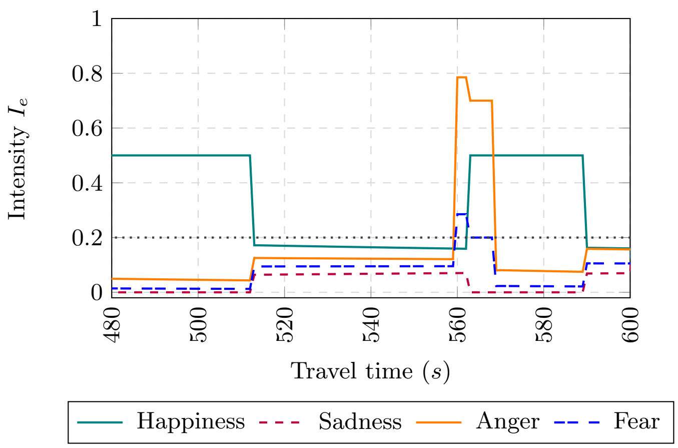

Figure 8: Intensity of emotions of an arbitrary driver during a part of the simulation. An emotion e is dominant at time step t, if its intensity I_e is greater than all other emotions, and exceeds the activation threshold $I_{th} = 0.2$ (dotted line).

5.4 Configuration 2B - Driver types and distraction triggering

In this simulation, different driver types are used again and are configured to experience randomly triggered distraction (according to chapter 3.1). With this configuration, the average speed of all vehicles decreases to 66.17 km/h and the average travel time increases to 780 s. It can also be seen that detector B shows very low speeds due to traffic congestion at the bottleneck. In contrast to simulation **1** and **2A** the congestion does not resolve, which can be explained with the distraction of the drivers.

Whenever a distraction is triggered vehicles keep their current speed and do not accelerate, due to the driver which rather concentrates on other tasks, such as using his phone, configuring his navigation system, or getting distracted by other passengers. This not only has effects on the usual traffic flow (as seen in the decreased speed at detector A), but especially on bottlenecks, where an efficient merging of vehicles onto one lane is required. In such cases, distracted vehicles disturb the merging process from time to time which eventually results in traffic congestion right before the bottleneck. For example, if a vehicle is required to accelerate in order to fill the front gap quickly, distracted drivers delay the following traffic flow by staying at their current position. Concluding, the consideration of distraction in the simulation is able to model complex traffic situations which have influences on the overall traffic flow.

6. CONCLUSION

In this paper, emotional processes and distraction factors of drivers were modelled within a microscopic traffic simulation environment. The emotional state of drivers was modelled with the help of the *robot-learning-method* by Gadanho and Hallam, in which each individual driver perceives the world through sensations which influence their emotions and therefore their decisions and behaviour. Also, each driver experiences temporary distractions in which the driver's reaction capabilities are decreased. Furthermore, drivers are parametrised individually based on current studies and investigations. Those concepts were studied and assessed with the help of simulation scenarios modelling typical urban commuter traffic on a motorway. The results show that all those concepts improve classic traffic simulations in terms of an individual behaviour of drivers. While a sophisticated parametrisation of drivers leads to a more diverse traffic in which vehicles form groups and produce short-term traffic congestion at bottlenecks, emotional processes result in unexpected behaviour of individual drivers, such as speeding or unusual lane changes. Furthermore, temporary distraction especially leads to inefficient merging at bottlenecks and therefore unexpected traffic congestion occurs, whereas classic simulations fail due to perfect and unrealistic models.

Since the results are promising, we plan to make further investigations with other simulation tools. For example, including those models in driving simulators. Also, the emotional model and distraction mechanisms used in our study need to be calibrated with real world data in order to get even more meaningful results.

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